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PIXEL CLASSIFICATION BASED ON GRAY LEVEL AND LOCAL "BUSYNESS"

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See 1473 in back

ABSTRACT

An image can be segmented by classifying its pixels using local properties as features. Two intuitively useful properties are the gray level of the pixel and the "busyness", or gray level fluctuation, measured in its neighborhood. Busyness values tend to be highly variable in busy regions; but great improvements in classification accuracy can be obtained by smoothing these values prior to classifying. An alternative possibility is to classify probabilistically and use relaxation to adjust the probabilities.

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1. Introduction

An image can often be usefully segmented into regions by classifying its pixels using local properties of the pixels as features. Properties that can be used for this purpose, in addition to the gray level of the pixel itself, include the gray levels of neighbors [1]; average gray levels measured over neighborhoods of various sizes [2]; and local measures of "busyness" [3]. Using such properties, one can attempt to segment an image into homogeneous regions each of which has characteristic first- and second- (or higher-) order gray level statistics.

Subjectively, the differences between regions in an image often seem to be expressible in terms of mean gray level and mean "busyness"; thus the feature pair (gray level, local busyness) is of special interest as a basis for segmentation [3]. However, busyness is hard to measure locally, and yields values which are highly variable even in a region that appears to be uniformly busy. Thus pixel classification based on local busyness value (together with gray level) is likely to make many errors in busy regions.

This paper studies the effectiveness of smoothing the local busyness values prior to using them for classification. It is shown that great reductions in error rate can be achieved this way. Results are compared for two different local busyness measures, based on two neighborhood sizes (3x3 and 5x5), using median filtering based on two neighborhood sizes (3x3 and 5x5). The use of probabilistic relaxation to improve the classification results is also investigated.

2. Busyness measures

In [3], local busyness was measured by "minimum total variation" (MTV). For the 3x3 neighborhood $\begin{matrix}a&b&c\\d&e&f\\g&h&i\end{matrix}$, this is defined by

$$\min[|a-b|+|b-c|+|d-e|+|e-f|+|g-h|+|h-i|,\\ |a-d|+|d-g|+|b-e|+|e-h|+|c-f|+|f-i|]$$

In other words, the "total variation" (sum of absolute gray level differences of all pairs of adjacent pixels in the neighborhood) is computed for horizontally adjacent pairs and for vertically adjacent pairs, and the min of the two is then taken. The min should be high in a busy neighborhood, where many adjacent pairs differ, but it should be low in a neighborhood containing a horizontal or vertical edge, since in such a neighborhood there are high horizontal differences but no high vertical ones, or vice versa. Thus the MTV measure should yield high values throughout a busy region, but not on edges between smooth regions.

An obvious defect of the MTV as just defined is that it does yield high values at pixels on oblique edges, where there are high differences in both directions. To alleviate this problem, we can take differences in the diagonal directions as well, and take a min over four directions. Note, however, that there are only four adjacent pairs in each diagonal direction in a 3x3 neighborhood--i.e., the sums of diagonal absolute differences are

$$|a-e|+|e-i|+|d-h|+|b-f| \quad \text{and} \quad |c-e|+|e-g|+|b-d|+|f-h|$$

Thus to define a four-direction MTV, we should use averages rather than sums, e.g.

$$\min\left[\tfrac{1}{6}(|a-b|+|b-c|+|d-e|+|e-f|+|g-h|+|h-i|),\right.$$
$$\tfrac{1}{6}(|a-d|+|d-g|+|b-e|+|e-h|+|c-f|+|f-i|),$$
$$\tfrac{1}{4}(|a-e|+|e-i|+|d-h|+|b-f|),$$
$$\left.\tfrac{1}{4}(|c-e|+|e-g|+|b-d|+|f-h|)\right]$$

Another possible measure of local busyness is the "median absolute difference" (MAD). For the 3x3 neighborhood, this is defined as the median of the absolute differences of all twelve pairs of horizontally or vertically adjacent pixels. In a busy region, the median should be about the same as the mean. On an edge between two smooth regions, on the other hand, the median should be low, since only a minority of the differences are high. For example, in the neighborhood $\begin{matrix}0&0&1\\0&1&1\\1&1&1\end{matrix}$, there are four differences of 1 (two horizontal and two vertical) and eight of 0, so that the median is 0 even for diagonal edges. Since this two-direction version of the MAD measure is insensitive to diagonal edges, a four-direction version was not used in our experiments.

Busyness measures based on a 3x3 neighborhood are bound to be highly variable, since there are only a few adjacent pairs of points in such a neighborhood. Improved results should be obtained when larger neighborhood sizes are used; but if we use large sizes, the border zones (where the neighborhoods overlap two or more regions) become large, and reliable feature values are hard to obtain in these zones. To study neighborhood size effects, we used 5x5 versions of the MTV and MAD measures. In a 5x5 neighborhood, MTV is defined in terms of 20 horizontal and 20 vertical adjacent pairs (as well as 16 adjacent pairs in each diagonal direction, if the four-direction definition is used), and MAD is defined in terms of 40 horizontal and vertical adjacent pairs; the details are straightforward.

3. Experiments

3.1 Test data and initial classification

The experiments in this paper made use of the house image shown in Figure 1, which was also used in [3-4]. This image contains five major types of regions--sky, brick, shadows (and roof), bushes, and grass. In order to characterize these regions with respect to the (gray level, local busyness) feature pair, the image was hand segmented, as shown in Figure 1, and mean vectors and covariance matrices for each class were computed; these are shown, for each of the busyness measures, in Table 1. We see that two of the classes, shadows and bushes, have nearly the same mean vector, even though the bushes appear to be much busyer than the shadows. This is especially true for the 3x3 MTV measures; the difference is greatest for the 5x5 MAD measure.

Assuming that the classes have bivariate Gaussian distributions with the given means and covariances, we can compute the maximum-likelihood classification of each pixel. Confusion matrices showing the resulting errors, for each busyness measure, are shown in Table 2. We see that the shadow pixels are almost all classified as bush when the 3x3 measures are used. This was to be expected, since the bush class has higher a priori probability (i.e., larger area in the hand segmentation), and is also more variable, so that its conditional probability drops more slowly than that of the shadow class with distance from the mean. The results are much better using the 5x5 measures.

3.2 Median filtering results

The classification results can be greatly improved if the busyness values are smoothed prior to clustering and classification. Two smoothing neighborhoods were used in our experiments, 3x3 and 5x5. The smoothing method used was median filtering, since it tends not to blur boundaries between regions. In the interior of a region, the median and mean should be approximately equal; but near a region border, the median will be insensitive to the values obtained from the neighbors on the other side of the border, while the mean will respond to these values. This remains true if the median filtering process is iterated.

Median filtering reduces the variability of the busyness values in each class, while preserving (at least approximately) the class means.* When the pixels are classified using these "tighter" class definitions, the error rates should be reduced. Tables 3-4 show the class error rates as functions of iteration number for the six busyness measures, using 3x3 and 5x5 median filtering, respectively. We see that there is little or no improvement over the initial good results obtained from the 5x5 measures. For the 3x3 measures, a few iterations of 3x3 filtering, or a single iteration of 5x5 filtering, yield a dramatic improvement, with error rates at least as low as those obtained from the 5x5 measures.

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* We applied median filtering only to the busyness values, not to the gray levels; applying it to both would presumably have yielded somewhat greater improvement in the classification results.

3.3 Relaxation results

Another possible way of improving the classification results is to classify the pixels probabilistically, and then use probabilistic relaxation [5] to iteratively adjust the probabilities before making the maximum-likelihood decision. This method was very effective [4] in improving pixel classifications based on color components in a color version of the house image--in fact, it was much more effective than smoothing the color values prior to classification.

The initial class probabilities used in the relaxation process are the same as those used for the maximum-likelihood classification. The compatibility coefficients in the relaxation formula were computed using mutual information estimates derived from the initial probabilities, as in [6]; this method was also used in [4].

Relaxation was found to be effective in reducing the error rate in our experiments, but no more so than median filtering prior to classification. Table 5 shows the class error rates as functions of iteration number (i.e., when the most probable class is chosen after the kth iteration, for k=0,1,2,...) for the six busyness measures, using relaxation based on a 3x3 neighborhood of each pixel. We see that the improvement in Class 4 is slower (or, for the 5x5 measures, begins late), but that eventually a higher level of correctness is achieved than with 3x3 median filtering (or even with 5x5, in most cases), but at the cost of an increase in the Class 5 errors.

Relaxation is also slightly effective in improving the classification results obtained after a few iterations of median filtering. Table 6 shows the results for the 3x3 four-direction MTV measure when we estimate the class probabilities after four iterations of 5x5 median filtering and then apply 3x3 relaxation. (There are some slight discrepancies in the initial values between Tables 5-6 and Tables 3-4, due to roundoff errors in the initial probability computations, which were done on two different computers).

4. Concluding remarks

Both median filtering and relaxation are effective in improving the accuracy of pixel classification based on gray level and busyness. When we use 3x3 busyness measures, median filtering yields an immediate improvement (especially for the 5x5 filter; Table 3a is an exception), followed in most cases (but see Table 4b) by a gradual deterioration as the process is iterated. Relaxation yields steady improvement for Class 4 over a larger number of iterations, but at the cost of some deterioration in Class 5. For the 5x5 busyness measures, median filtering yields no improvement, but relaxation does; and it also provides some improvement if it is applied after a few iterations of median filtering.

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Figure 1. House picture (bottom) and hand segmentation into five classes (top). The classes are brick, sky, grass, shadows, and bushes.

Measure	1 (brick)	2 (sky)	3(grass)	4(shadows)	5 (bushes)
a) 3x3 MTV, two directions	.32	.63	.27	.84	1.15
b) 3x3 MTV, four directions	.40	.63	.42	.92	1.20
c) 3x3 MAD	.40	.58	.42	1.00	1.28
d) 5x5 MTV, two directions	.47	.69	.45	1.06	1.36
e) 5x5 MTV, four directions	.44	.68	.44	1.03	1.33
f) 5x5 MAD	.37	.49	.44	.89	1.24
Mean gray level	29.21	44.29	33.33	18.95	20.55

Table 1a. Mean vectors for the five classes using each of the six busyness measures.

Measure					
a)	-.11 .45	-2.68 1.74	-.18 .23	1.57 1.62	.95 .72
b)	-.08 .43	-2.73 1.72	-.18 .29	1.54 1.50	.77 .56
c)	-.13 .43	-3.00 1.64	-.24 .31	1.42 1.65	.92 .73
d)	-.13 .49	-2.34 1.46	-.21 .28	1.36 1.49	.66 .41
e)	-.12 .47	-2.37 1.46	-.21 .27	1.39 1.48	.62 .39
f)	-.10 .31	-2.13 .86	-.21 .25	.65 .74	.54 .30
(Gray level, gray level) covariance	1.93	17.91	2.92	16.39	28.86

Table 1b. Covariance matrices for the five classes using each of the six busyness measures (a-f, as in Table 1a). The first number is the (gray level, busyness) covariance, and the second is (busyness, busyness).

a)	.92	.00	.02	.00	.05
	.01	.94	.02	.00	.03
	.11	.00	.87	.00	.01
	.02	.00	.00	.04	.93
	.09	.01	.00	.01	.89
b)	.92	.00	.02	.00	.05
	.01	.94	.03	.00	.02
	.11	.00	.87	.00	.01
	.02	.01	.00	.06	.91
	.08	.00	.01	.02	.88
c)	.93	.00	.02	.00	.05
	.01	.93	.03	.00	.03
	.11	.00	.88	.00	.01
	.02	.00	.00	.04	.93
	.08	.00	.01	.02	.89
d)	.92	.00	.02	.00	.05
	.01	.94	.02	.00	.04
	.12	.00	.88	.00	.01
	.02	.00	.00	.53	.44
	.08	.01	.00	.04	.87
e)	.93	.00	.02	.00	.05
	.01	.94	.02	.00	.03
	.12	.00	.88	.00	.01
	.02	.00	.00	.54	.43
	.08	.00	.00	.04	.87
f)	.90	.00	.05	.00	.05
	.01	.94	.02	.00	.03
	.08	.00	.92	.00	.00
	.02	.00	.00	.40	.57
	.06	.01	.01	.04	.88

Table 2. Confusion matrices for initial classifications using each of the six busyness measures (a-f). The entry in the ith row and jth column is the fraction of the time a pixel in class i was assigned to class j, $1 \le i,j \le 5$.

a)

Iteration	Class 1	2	3	4	5
0	.92	.94	.87	.04	.89
1	.91	.94	.88	.04	.90
2	.92	.94	.88	.24	.84
3	.92	.94	.88	.49	.83
4	.92	.94	.88	.56	.83
5	.92	.94	.87	.58	.83
6	.92	.94	.87	.58	.83
7	.92	.94	.87	.59	.83

b)

Iteration	Class 1	2	3	4	5
0	.92	.94	.87	.06	.88
1	.90	.94	.92	.54	.87
2	.90	.94	.92	.54	.87
3	.90	.94	.92	.53	.87
4	.90	.94	.92	.53	.87
5	.90	.94	.92	.53	.87
6	.91	.94	.92	.52	.88
7	.91	.94	.92	.52	.88

Table 3. Class error rates as functions of iteration number for the six busyness measures (a-f) using 3x3 median filtering.

c)

Iteration	Class 1	2	3	4	5
0	.93	.93	.88	.04	.89
1	.90	.93	.92	.45	.86
2	.90	.93	.92	.46	.86
3	.90	.94	.92	.45	.87
4	.91	.94	.92	.43	.87
5	.91	.94	.92	.42	.87
6	.91	.94	.92	.41	.87
7	.91	.94	.92	.40	.87

d)

Iteration	Class 1	2	3	4	5
0	.92	.94	.88	.53	.87
1	.92	.94	.88	.52	.88
2	.92	.94	.88	.52	.88
3	.92	.94	.88	.52	.89
4	.92	.94	.88	.52	.89
5	.92	.94	.88	.52	.89
6	.92	.94	.88	.52	.89
7	.92	.94	.88	.52	.89

Table 3, continued.

e)

Iteration	Class 1	2	3	4	5
0	.93	.94	.88	.54	.87
1	.92	.94	.88	.53	.88
2	.92	.94	.88	.54	.88
3	.92	.94	.88	.53	.88
4	.92	.94	.88	.53	.88
5	.90	.94	.93	.53	.88
6	.90	.94	.93	.53	.88
7	.90	.94	.93	.54	.88

f)

Iteration	Class 1	2	3	4	5
0	.90	.94	.92	.40	.88
1	.90	.94	.92	.39	.88
2	.91	.94	.93	.38	.88
3	.91	.94	.93	.38	.88
4	.91	.93	.93	.38	.88
5	.91	.93	.93	.39	.88
6	.91	.93	.93	.39	.88
7	.91	.93	.93	.39	.88

Table 3, continued.

a)

Iteration	Class 1	2	3	4	5
0	.92	.94	.87	.04	.89
1	.92	.94	.87	.59	.82
2	.93	.94	.87	.59	.83
3	.93	.94	.87	.59	.83
4	.93	.94	.87	.59	.83
5	.92	.93	.87	.58	.86
6	.92	.93	.87	.58	.85
7	.92	.93	.87	.58	.85

b)

Iteration	Class 1	2	3	4	5
0	.92	.94	.87	.06	.88
1	.91	.94	.92	.53	.87
2	.91	.94	.92	.61	.82
3	.90	.94	.92	.63	.83
4	.90	.93	.93	.65	.83
5	.90	.93	.93	.66	.82
6	.91	.93	.93	.66	.82
7	.91	.92	.93	.66	.83

Table 4. Analogous to Table 3, using 5x5 median filtering.

c)

Iteration	Class 1	2	3	4	5
0	.93	.93	.88	.04	.89
1	.91	.94	.92	.44	.87
2	.92	.93	.93	.43	.86
3	.90	.93	.93	.43	.90
4	.90	.93	.93	.47	.87
5	.91	.92	.93	.48	.85
6	.91	.92	.93	.48	.84
7	.91	.91	.93	.47	.84

d)

Iteration	Class 1	2	3	4	5
0	.92	.94	.88	.53	.87
1	.92	.94	.88	.52	.89
2	.89	.93	.93	.51	.91
3	.89	.93	.93	.51	.91
4	.89	.93	.93	.50	.91
5	.90	.93	.93	.49	.92
6	.90	.93	.93	.48	.92
7	.90	.92	.93	.48	.91

Table 4, continued.

		Class				
e)	Iteration	1	2	3	4	5
	0	.93	.94	.88	.54	.87
	1	.90	.94	.93	.53	.89
	2	.89	.93	.93	.52	.90
	3	.90	.93	.93	.52	.91
	4	.90	.94	.93	.50	.91
	5	.90	.93	.93	.50	.91
	6	.90	.93	.93	.49	.91
	7	.90	.93	.93	.49	.90

		Class				
f)	Iteration	1	2	3	4	5
	0	.90	.94	.92	.40	.88
	1	.91	.93	.93	.37	.88
	2	.91	.93	.93	.38	.88
	3	.91	.92	.93	.38	.88
	4	.91	.92	.93	.38	.88
	5	.92	.92	.93	.38	.87
	6	.92	.92	.93	.37	.87
	7	.92	.92	.93	.37	.87

Table 4, continued.

a)	Iteration	Class 1	2	3	4	5
	0	.92	.94	.86	.04	.89
	1	.93	.93	.87	.04	.89
	2	.93	.93	.88	.05	.89
	3	.93	.93	.88	.06	.89
	4	.93	.93	.88	.06	.89
	5	.93	.93	.88	.07	.88
	6	.93	.93	.88	.07	.88
	7	.93	.93	.88	.07	.88
	8	.93	.93	.88	.20	.87
	9	.93	.93	.88	.37	.82
	10	.93	.93	.88	.46	.80
	11	.93	.93	.88	.48	.79
	12	.93	.93	.88	.53	.78
	13	.93	.93	.89	.56	.78
	14	.93	.93	.89	.58	.77
	15	.93	.93	.89	.59	.76
	16	.93	.93	.89	.61	.76

Table 5. Analogous to Table 3, using 3x3 relaxation applied to the initial class probabilities.

b) Iteration	Class 1	2	3	4	5
0	.92	.94	.86	.06	.87
1	.93	.92	.87	.06	.87
2	.93	.92	.88	.07	.88
3	.93	.92	.88	.07	.87
4	.94	.92	.88	.16	.87
5	.94	.92	.88	.33	.84
6	.94	.92	.88	.41	.82
7	.94	.92	.88	.47	.82
8	.94	.92	.88	.50	.82
9	.94	.92	.88	.52	.81
10	.94	.92	.88	.54	.81
11	.94	.92	.88	.55	.80
12	.94	.92	.88	.55	.80
13	.94	.92	.88	.55	.80
14	.94	.92	.88	.56	.79
15	.94	.92	.88	.57	.79
16	.94	.92	.88	.58	.78

Table 5, continued.

c) Iteration	Class 1	2	3	4	5
0	.92	.93	.86	.04	.83
1	.94	.92	.88	.04	.83
2	.94	.92	.89	.05	.83
3	.94	.92	.89	.05	.84
4	.94	.92	.89	.06	.84
5	.94	.92	.89	.07	.84
6	.94	.92	.89	.08	.84
7	.94	.92	.89	.27	.85
8	.94	.92	.89	.33	.84
9	.94	.92	.89	.41	.85
10	.94	.92	.89	.45	.85
11	.94	.92	.89	.48	.85
12	.94	.92	.89	.49	.85
13	.94	.92	.89	.50	.85
14	.94	.92	.89	.50	.85
15	.94	.92	.89	.50	.85
16	.94	.92	.89	.51	.85

Table 5, continued.

d)

Iteration	Class 1	2	3	4	5
0	.92	.94	.86	.53	.86
1	.92	.92	.88	.52	.86
2	.92	.92	.89	.52	.87
3	.93	.92	.89	.51	.87
4	.93	.92	.89	.52	.86
5	.93	.92	.89	.52	.86
6	.93	.92	.89	.53	.86
7	.93	.92	.89	.53	.86
8	.93	.92	.89	.54	.86
9	.93	.92	.89	.55	.86
10	.93	.92	.89	.56	.85
11	.93	.92	.89	.57	.85
12	.93	.92	.89	.58	.85
13	.93	.92	.89	.60	.85
14	.93	.92	.89	.61	.84
15	.93	.92	.89	.63	.84
16	.93	.92	.89	.64	.83

Table 5, continued.

e) Iteration	Class 1	2	3	4	5
0	.92	.94	.86	.54	.86
1	.92	.92	.88	.54	.87
2	.92	.92	.89	.53	.87
3	.93	.92	.89	.53	.87
4	.93	.92	.89	.53	.87
5	.93	.92	.89	.53	.86
6	.93	.92	.89	.54	.86
7	.93	.92	.89	.55	.86
8	.93	.92	.89	.56	.86
9	.93	.92	.89	.56	.86
10	.93	.92	.89	.57	.85
11	.93	.92	.89	.59	.85
12	.93	.92	.89	.60	.85
13	.93	.92	.89	.61	.85
14	.93	.92	.90	.63	.84
15	.93	.92	.90	.64	.84
16	.93	.92	.90	.65	.83

Table 5, continued.

f)	Iteration	Class 1	2	3	4	5
	0	.90	.94	.91	.39	.87
	1	.93	.92	.90	.39	.87
	2	.93	.92	.90	.39	.87
	3	.93	.92	.90	.39	.88
	4	.93	.92	.91	.39	.87
	5	.93	.92	.91	.39	.87
	6	.94	.92	.91	.39	.87
	7	.94	.92	.91	.39	.87
	8	.94	.92	.91	.39	.87
	9	.94	.92	.91	.40	.87
	10	.94	.92	.91	.41	.87
	11	.94	.92	.91	.43	.86
	12	.94	.92	.91	.45	.86
	13	.94	.92	.91	.47	.85
	14	.94	.92	.91	.49	.84
	15	.94	.92	.91	.50	.83
	16	.94	.92	.91	.51	.82

Table 5, continued.

Iteration	Class 1	2	3	4	5
0	.93	.94	.86	.57	.83
1	.93	.93	.85	.57	.85
2	.94	.92	.85	.57	.85
3	.94	.92	.86	.57	.85
4	.94	.92	.86	.57	.85
5	.94	.92	.86	.57	.85
6	.94	.92	.86	.58	.85
7	.94	.92	.86	.58	.85
8	.94	.92	.86	.58	.85
9	.94	.92	.86	.58	.84
10	.94	.92	.86	.58	.84
11	.94	.92	.86	.59	.83
12	.94	.92	.86	.60	.82
13	.94	.92	.86	.61	.81
14	.94	.92	.86	.62	.81
15	.94	.92	.86	.62	.80
16	.94	.92	.86	.63	.80

Table 6. Analogous to Table 5a, but with relaxation applied to the class probabilities estimated after four iterations of 5x5 median filtering.

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An image can be segmented by classifying its pixels using local properties as features. Two intuitively useful properties are the gray level of the pixel and the "busyness", or gray level fluctuation, measured in its neighborhood. Busyness values tend to be highly variable in busy regions; but great improvements in classification accuracy can be obtained by smoothing these values prior to classifying. An alternative possibility is to classify probabilistically and use relaxation to adjust the probabilities.